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Predicting the abatement rates of soil organic carbon sequestration management in Western European vineyards using random forest regression

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ABSTRACT

The implementation of soil organic carbon sequestration (SCS) practices on agricultural land has the potential to help to mitigate climate change at the global level. However, our understanding of the extent to which viticultural soils can contribute to this global effort remains limited. In this study, we used a random forest regression to predict the change in soil organic carbon stocks in vineyards of Western Europe under five SCS practices: organic amendments (OA), cover cropping (CC), organic amendments and no-tillage (OA+NT), no-tillage and cover cropping (NT+CC), and a combination of organic amendments, no-tillage and cover cropping (OA+NT+CC). The abatement rate of each SCS practice was modelled and mapped for six countries in Western Europe: Spain, France, Italy, Portugal, Germany and Austria. Overall, the highest abatement rate was reached under OA+NT+CC (8.29 Mg CO_2-eq. ha^{-1} yr^{-1}), whereas the lowest was observed under CC (7.03 Mg CO_2-eq. ha^{-1} yr^{-1}). Results showed major differences in abatement rates at the regional and national level. Despite these differences, the adoption of SCS practices was associated with a high abatement potential in the six countries and should be encouraged in the viticulture sector as a way to offset greenhouse gas emissions via soil carbon sequestration.

1. Introduction

Soil carbon sequestration in agricultural soils has the potential to contribute substantially to mitigating climate change, provided that specific changes in soil management are implemented (Smith, 2016). Soil organic carbon (SOC) is the largest pool of organic carbon (OC) in terrestrial ecosystems, containing globally over 1,500 Pg C in the upper 1-m layer of soil, which is more than the carbon stock in the above-ground vegetation and the atmosphere combined (FAO and ITPS, 2015). About 45% of global soils are used for agriculture, either under the form of cropland or grassland (Paustian et al., 2019); changes in SOC content in these soils can, therefore, have profound impacts on climate change mitigation. The mitigation potential of soil carbon sequestration (SCS) practices (including biochar) was estimated to range from 4 to 6 Pg CO_2-eq. yr^{-1} at the global level (Smith, 2016). Paustian et al. (2016) suggested that the maximum mitigation potential of SCS practices could even be as high as 8 Pg CO_2-eq. yr^{-1}, while in a more recent review of the literature Fuss et al. (2018) showed that it would more likely be 7 Pg CO_2-eq. yr^{-1}. For comparison, UNEP (2018) estimated total anthropogenic emissions to be 53.5 Pg CO_2-eq. yr^{-1} in 2017. This indicates that soil carbon sequestration in agricultural soils could offset up to 13% of global greenhouse gas emissions annually.

Despite the widespread comprehension of SCS practices in the agriculture sector (Sykes et al., 2020), information about soil carbon sequestration in vineyard agroecosystems remains sparse. Yet, changes in soil management practices have an important potential to increase carbon sequestration in viticultural soils. Payen et al. (2021) showed in their meta-analysis that the SOC sequestration rate of SCS practices in vineyards could be as high as 11.06 Mg CO_2-eq. ha^{-1} yr^{-1} for a combination of organic amendments and no-tillage. This high SOC sequestration rate could be due to the particularly low OC levels in vineyards under conventional management (Eldon and Gershenson, 2015). Enhancing SOC sequestration in vineyard agroecosystems, thus, represents a promising strategy for mitigating climate change in countries with an important

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land area dedicated to viticulture. SOC sequestration in viticultural soils could, more precisely, play an important role in greenhouse gas offsetting at the regional level, in areas where viticulture represents a substantial share of the agricultural land use. This is the case for the Languedoc-Roussillon region in France, for instance, where viticulture represents 26% (*i.e.* 233,069 ha) of the regional total agricultural land (*i.e.* 882,995 ha) and grapevine is the most cultivated crop, with 62% of the agricultural farms in the region growing grapevine (Agreste Languedoc-Roussillon, 2015).

Since the equilibration of SOC after a change in management takes several decades, a deeper understanding of the expected changes in SOC stocks associated with SCS practices is needed if these practices are to be implemented as long-term strategies to mitigate climate change. Many tools have been developed to predict the changes in SOC stocks under diverse soil management in various agroecosystems. Process-based models, including RothC (Coleman and Jenkinson, 1996), ECOSSE (Smith et al., 2010) and DALEC (Bloom and Williams, 2015), have been developed and run to project changes in SOC over different timeframes for different soil management. These models have the advantage to overcome the issues associated with costly and extensive field experiments (Francaviglia et al., 2012). Statistical techniques, such as linear mixed models (Doetterl et al., 2013), partial least square regressions (Amare et al., 2013) and multiple linear regressions (Meersmans et al., 2008), have also been applied to estimate and map SOC stocks. More recently, new methods from the machine learning field have been adapted to the context of SOC stock prediction. They include random forest regressions (Grimm et al., 2008), support vector machines (Viscarra Rossel and Behrens, 2010) and artificial neural networks (Aitkenhead and Coull, 2016). Machine-learning approaches bear the advantage of overcoming flaws of parametric and non-parametric statistical methods, such as overfitting, non-linearity and autocorrelation (Drake et al., 2006), which improves the prediction accuracy of spatial models (Were et al., 2015).

There have been few attempts at modelling changes in SOC stocks under SCS management in vineyard agroecosystems. Bleuler et al. (2017) applied the RothC model to predict the effects of SCS management on SOC stocks under different crop types, including vines. However, their analysis only considered two SCS practices (compost addition and cover cropping), while other SCS practices applicable to viticulture (such as returning pruning residues to the soil, implementing no-tillage, and applying biochar amendments to the soil) were not considered in the study. Their study area was also limited to the Foggia province in southern Italy. Similarly, other modelling studies including viticultural soils only took into account a few SCS practices (*e.g.*, no-tillage coupled with cover cropping in Francaviglia et al., 2012, or compost amendment in Mondini et al., 2012) and were limited to very specific regions within wine-producing countries (*e.g.*, to the north-east of Sardinia, Italy in Francaviglia et al., 2012, or Spain's Mediterranean coastal areas in Pardo et al., 2017).

There is a need to extend the modelling of SOC change under SCS management in vineyards to all the SCS practices applicable to vineyard agroecosystems and to all the different types of climate where viticulture is conducted. The aim of this paper is (i) to develop a model based on a machine-learning approach to estimate the annual change in SOC stocks in vineyards under SCS management relative to conventional practices and (ii) to predict the annual change in SOC stocks in vineyards for a set of specific SCS practices and map the results for the winegrowing regions of six European countries (Spain, France, Italy, Portugal, Germany and Austria) representative of viticulture in Western Europe.

2. Materials and methods

2.1. Study area

Six European countries were chosen to predict and map the change in SOC stocks under SCS management in vineyards: Spain, France, Italy, Portugal, Germany and Austria. These countries were selected due to their important land area dedicated to viticulture: 0.969 Mha in Spain, 0.793 Mha in France, 0.705 Mha in Italy, 0.192 in Portugal, 0.103 in Germany and 0.049 Mha in Austria in 2018 (OIV, 2019). They represent 82% of the viticultural land of the European Union and 35% of the total viticultural land worldwide. These countries also present a good variety of climates (Mediterranean, oceanic, continental, etc.) under which viticulture is undertaken.

2.2. Building the random forest model using data from field experiments

2.2.1. Data collection

The data used for model building was retrieved from soil experiments reporting the change in SOC content in vineyards under specific SCS management relative to conventional management and was collected by literature search. A complete description of the methodology used for the data collection is available in Payen et al. (2021). The literature search yielded a total of 146 comparisons between SCS management and conventional management in vineyards. Five different SCS practices were gathered in the literature search: the use of organic amendments (OA), the use of biochar amendments (BC), incorporating the pruning residues to the soil (PR), no-tillage (NT), and cover cropping (CC). Depending on the studies, these practices were used in field experiments individually or as a combination of two or three SCS practices (*e.g.*, NT+CC or OA+NT+CC).

2.2.2. Response variables

Two rates measuring the change in SOC stocks were calculated from the collected data and used as response variables in the model: the SOC stock rate of change and the SOC sequestration rate. The SOC stock rate of change (R), expressed in yr^{-1}, was calculated by the methods of Hedges et al. (1999) and Abdalla et al. (2018) following Equation (1), where $(SOC\ stock)_f$ corresponds to the SOC stock (in Mg C ha^{-1}) at the end of the experiment under a specific SCS practice, $(SOC\ stock)_i$ to the SOC stock at the beginning of the experiment and t to the duration of the field experiment (in yr). The SOC sequestration rate (in Mg C ha^{-1} yr^{-1}) was calculated following Equation (2).

$$R = \frac{\ln\left((SOC\ stock)_f / (SOC\ stock)_i\right)}{t} \tag{1}$$

$$SOC\ sequestration\ rate = \frac{(SOC\ stock)_f - (SOC\ stock)_i}{t} \tag{2}$$

The SOC stock rate of change was modelled without further transformation, whereas the values of the SOC sequestration rate were first normalised using a feature scaling method: the range of values was rescaled into [0, 1] following Equation (3), where x' represents the SOC sequestration rate value rescaled, x the SOC sequestration rate value calculated, x_{min} the minimum value of the SOC sequestration rate in the dataset, and x_{max} the maximum value. The natural logarithm function was then applied to the results of the feature scaling to obtain a normal distribution of the values. Once the model was trained, the actual and predicted values were back-transformed for analysis.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

2.2.3. Explanatory variables

Fourteen explanatory variables were included in the model:

- **Soil texture (in %).** Sand and Clay constituted two explanatory variables representing the soil texture of the experiment. Silt was not included in the model, since it decreased the overall predictive power of the model and its value is correlated to the value of Sand and Clay. Percentages of Sand and Clay of each field experiment were extracted from the world raster soil grids created by Hengl et al. (2017) and available on the ISRIC – World Soil Information website, using geographic coordinates. The raster grids had a resolution of 250 m × 250 m for a soil depth of 30 cm.

- **Bulk density (in kg m^{-3}).** The bulk density of each field experiment was extracted from the world raster soil grid created by Hengl et al. (2017). The raster grid had a resolution of 250 m × 250 m for a soil depth of 30 cm.
- **Initial SOC stock (in Mg C ha^{-1}).** The initial SOC stock was given in a few studies; in studies where it was not available, it was calculated using the SOC concentration, bulk density and soil depth. The complete methodology is described in Payen et al. (2021).
- **Mean annual air temperature (in °C) and mean annual precipitation (in mm).** Both were retrieved from the world raster climate data grids developed by Fick and Hijmans (2017) and available on the WorldClim – Global Climate Data website. The raster grids had a resolution of 1 km × 1 km.
- **Slope (in %).** The field experiment slope was calculated using the world raster soil databases available on the Food and Agriculture Organisation of the United Nations website (Fischer et al., 2008). The databases consisted in eight raster files corresponding to a different slope class: 0% ≤ slope ≤ 0.5%, 0.5% ≤ slope ≤ 2%, 2% ≤ slope ≤ 5%, 5% ≤ slope ≤ 10%, 10% ≤ slope ≤ 15%, 15% ≤ slope ≤ 30%, 30% ≤ slope ≤ 45%, and slope > 45%. Each raster file provided, for each cell, the percentage of land with a slope included in the different slope classes. The raster grids had a resolution of 10 km × 10 km. The overall slope for each comparison in the dataset was retrieved by summing the percentages extracted from each raster file multiplied by the mean value of the slope class.
- **Potential evapotranspiration (in mm day^{-1}).** The potential evapotranspiration (PET) of each field experiment was extracted from the world raster soil grid developed by Trabucco and Zomer (2018) and available on the CGIAR – Consortium for Spatial Information website. The raster grid had a resolution of 1 km × 1 km for a soil depth of 30 cm.
- **SCS practice.** Each single SCS practice (OA, BC, PR, NT and CC) was implemented in the model as an explanatory binary variable. It was coded 1 if the practice was implemented in the field experiment, 0 if it was not. This allowed the different combined SCS practices to be integrated into the model easily.
- **Duration of the experiment (in yr).** The length of the field experiment was provided in all studies.

2.2.4. *Random forest regression*

A random forest (RF) regression was used to model the SOC stock rate of change and SOC sequestration rate under SCS management. RF regression is a machine-learning algorithm, proposed by Breiman (2001) and popularly applied to the fields of yield prediction in precision agriculture (*e.g.*, Iqbal et al., 2018), soil parameters quantification (*e.g.*, de Santana et al., 2018), and soil organic matter stock estimation and mapping (*e.g.*, Wiesmeier et al., 2011). It is commonly used to aid in the selection of optimal variables when the number of variables is substantial and needs to be reduced to the most influential variables only. The RF algorithm uses a bootstrapping method based on the classification and regression tree analysis to predict a continuous response variable (Iqbal et al., 2018). It fits a collection of decision tree models to the dataset. Each tree, trained using different bootstrap samples of the training data, acts as a regression function on its own and the final output given by the regression corresponds to the average of the individual tree outputs (Adusumilli et al., 2013). The samples that are not in the bootstrap sample are called out-of-bag (OOB) samples; they are used to test the accuracy of the decision trees and estimate the overall model's misclassification error and variable importance (Adam et al., 2014).

Due to its cross-validation capability, RF regression provides realistic prediction error estimates during the training process, which makes it suitable for real-time implementation (Adusumilli et al., 2013). It is also largely insensitive to noisy datasets and has a good predictive capability for high dimensional datasets (Breiman, 2001). Other advantages of RF include its minimised risk of overfitting, the possibility to include categorical along with continuous explanatory variables, and the small number of model parameters that need to be specified comparatively to other modelling approaches (Hutengs and Vohland, 2016). RF also provides several metrics to aid in interpretation: for instance, it automatically computes a variable importance score that assesses the contribution of individual predictors to the final model. This makes random forests more interpretable than other modelling methods such as artificial neural networks (Prasad et al., 2006).

The RF regression was implemented within the R environment software (R Core Team, 2019), using the 'tidyverse' (Wickham et al., 2019), 'randomForest' (Liaw and Wiener, 2002), and 'caret' (Kuhn, 2020) packages. The predictive power and stability of the model were, for each response variable, validated by ten-fold cross-validation (James et al., 2017). The accuracy and predictive power of the RF regression were measured by four indicators: the root mean square error (RMSE), the mean absolute error (MAE), the mean square error (MSE), and the predictive coefficient of determination (R^2 or Var_{ex}). These indicators also served to identify which response variable was the most suitable for predicting change in SOC stocks in viticultural soils.

The RMSE and the MAE were calculated according to Equations (4) and (5), respectively, where $z'(x_i)$ corresponds to the predicted output for a given input sample x_i, z_i to the observed output for the same input sample x_i, and n to the total number of OOB samples in the regression. RMSE assessed the accuracy of the model predictions, whereas MAE determined the bias of the predictions (Wiesmeier et al., 2011). The RMSE was also normalised (NRMSE) by the mean for the two response variables so they could be compared. The model's misclassification error was obtained by calculating the MSE according to Equation (6). The MSE estimated how effective the model would be at predicting the response variable when exposed to new samples (Adusumilli et al., 2013). The percentage of explained variance Var_{ex} (or R^2) was calculated following Equation (7), where Var_z stands for the total variance of the response variable (Wiesmeier et al., 2011). Var_{ex} was used to evaluate the fit of the regression.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(z_i - z'(x_i))^2}{n}} \tag{4}$$

$$MAE = \sum_{i=1}^{n} \frac{(z_i - z'(x_i))}{n} \tag{5}$$

$$MSE = n^{-1} \sum_{i=1}^{n} (z'(x_i) - z_i)^2 \tag{6}$$

$$Var_{ex} = 1 - \frac{MSE}{Var_z} \tag{7}$$

To improve the classification accuracy of the model, the RF parameters – *i.e.* the number of trees built in total by the algorithm (n_{tree}) and the number of random input variables used to build each tree (m_{try}) – were optimised for the two response variables based on the OOB estimate of error, similarly as in Adam et al. (2014). The importance of the different explanatory variables as predictors of SOC stock change in the model was also measured using the percentage increase in the MSE (%IncMSE), which assesses, for each explanatory variable, how much the model accuracy decreases when that variable is dropped (Iqbal et al., 2018). A high change in %IncMSE when a variable is permuted means that this variable plays an important role in the model prediction (Prasad et al., 2006; Siroky, 2009).

2.3. *Predicting and mapping the total change in SOC stocks under different SCS practices*

The different steps described below were conducted in the R environment software (R Core Team, 2019), using the 'tidyverse' (Wickham et al., 2019) and 'raster' (Hijmans, 2019) packages. Once the raster files were created, the ArcGIS software (ESRI, 2019) was used to generate the final maps.

2.3.1. Input data for prediction and mapping

The CORINE Land Cover 2018, version 20, was used to identify and isolate land use dedicated to viticulture in the six countries. The CORINE database provides an inventory of all the different land uses in the European Union, classified in 44 classes and presented as a cartographic raster file with a resolution of 100 m × 100 m in the ETRS89/LAEA1052 standard European coordinate reference system (EEA, 2020). It was projected into the WGS 84, EPSG:4326 standard world coordinate reference system (NGA, 2019) so that geographic coordinates could be retrieved and used.

Digital shapefiles of each winegrowing region of the six countries were then created, using ArcGIS (ESRI, 2019), to group vineyards displayed on the CORINE Land Cover into the winegrowing regions they belong to. This allowed us to analyse how the changes in SOC stocks under SCS management varied between winegrowing regions, which are characterised by different soil composition, initial SOC content, climate, etc., and to investigate the reasons at the root of these variations. A total of 81 shapefiles were created (15 for Spain, 16 for France, 20 for Italy, 13 for Portugal, 13 for Germany and 4 for Austria) and used to reclassify the CORINE Land Cover with codes for each winegrowing region. The geographic coordinates of each raster cell corresponding to a vineyard were extracted for each winegrowing region. An overall data frame of 5,804,376 observations was obtained, giving the longitude and latitude of all the vineyards located in Spain, France, Italy, Portugal, Germany and Austria, along with a code specifying the winegrowing region of each set of coordinates.

These coordinates were used to extract the input data for the model from raster maps. Soil texture, bulk density, mean annual air temperature, mean annual precipitation and slope were extracted from the same raster grids as presented in section 2.2.3. Initial SOC stock was extracted from the raster soil grids developed by Hengl et al. (2017).

2.3.2. Predictions and mapping

The RF model was used to generate the predictions of change in SOC stocks for the 5,804,376 sets of coordinates retrieved. The SOC stock rate of change was chosen as a response variable, since it was associated with a higher predictive power and accuracy than the SOC sequestration rate (see section 3.1.2.). The duration variable was set at 20 years for all predictions, since it is assumed, under the IPCC (2006) guidelines, that SOC stocks, following a change in soil management, stabilise after twenty years. Five different combinations of SCS practices were modelled: OA, CC, OA+NT, NT+CC and OA+NT+CC.

To make the results more comparable with the emission reduction targets of the Paris Agreement and to re-contextualise SCS practices as greenhouse gas removal technologies, the RF predictions were converted into abatement rate (AR), which corresponds to the total annual increase in SOC stocks per hectare expressed in CO_2 equivalent of C (Mg CO_2-eq. ha^{-1} yr^{-1}). The AR was calculated following Equation (8), where *iSOC* corresponds to the initial SOC stock for a specific set of coordinates (in Mg C ha^{-1}) and *R* to the SOC stock rate of change (in yr^{-1}).

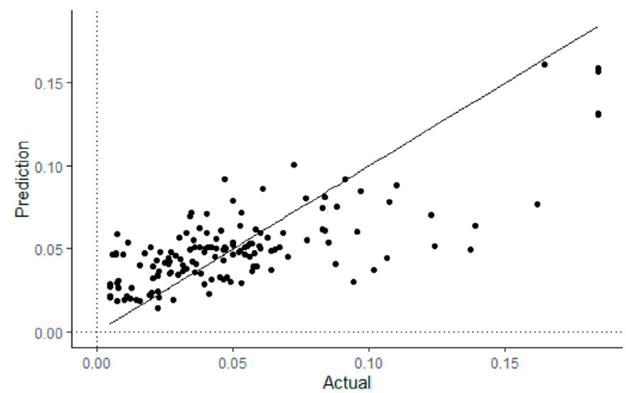
$$AR = iSOC \times (\exp(R) - 1) \times 44/12 \tag{8}$$

These predictions were used to (i) estimate the average abatement rate of each SCS practice at the regional and national level, (ii) estimate the total abatement potential of viticultural land in Spain, France, Italy, Portugal, Germany and Austria for each SCS practice, and (iii) map the abatement rate associated with the use of SCS management in vineyards in these wine-producing countries. (i) The average abatement rate for each winegrowing region ($AR_{\text{winegrowing region}}$) was calculated using Equation (9), where $AR_{winegrowing\ region}$ corresponds to the average abatement rate for a specific SCS practice in a given winegrowing region (in Mg CO_2-eq. ha^{-1} yr^{-1}), $area_i$ to the size of a given vineyard cell *i* (in ha), AR_i to the abatement rate associated with a given vineyard cell *i* (in Mg CO_2-eq. ha^{-1} yr^{-1}), and *n* to the total number of vineyard cells in a given winegrowing region. The average abatement rate at the national level (AR_{country}) was also calculated for the six countries using Equation (9), where *n* stands for the total number of vineyard cells in a given country. $AR_{\text{winegrowing region}}$ and AR_{country} are valid for a period of 20 years and a soil depth of 30 cm. (ii) The abatement potential (in Tg CO_2-eq. yr^{-1}) of the total viticultural land in the six countries, noted $AP_{country}$, was calculated for each SCS practice, using Equation (10). It was assumed that the SCS practices would be adopted in all vineyards and the current adoption rates of the practices were ignored. (iii) Five raster files, one for each SCS practice, were created and mapped at the European level. They displayed the predicted AR for each set of coordinates from the data frame.

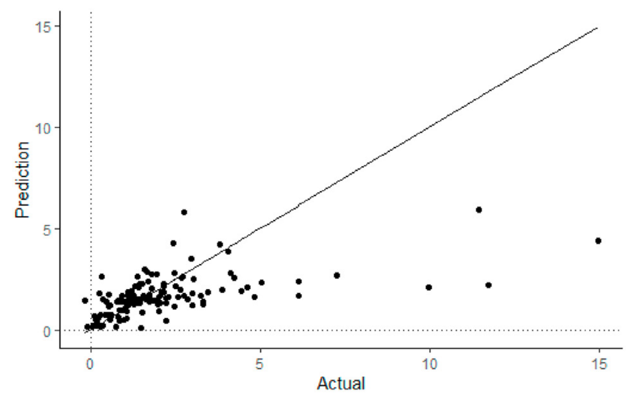
$$AR_{\text{winegrowing } region} = \frac{\sum_{i=1}^{n} area_i \times AR_i}{\sum_{i=1}^{n} area_i} \tag{9}$$

Table 1
Performance of the RF regression in modelling changes in SOC stocks.

Indicator	SOC stock rate of change (yr^{-1})	SOC sequestration rate (Mg C ha^{-1} yr^{-1})
RMSE	0.0253	1.6498
NRMSE	0.4979	0.8472
MAE	0.0190	0.9166
MSE	0.0006	0.3659
R^2	0.58	0.52



(a)



(b)

Fig. 1. Scatter plot representing the performance of the RF regression in predicting the SOC stock rate of change (a) and SOC sequestration rate (b). The values predicted by the RF model are compared to the measured values of the response variables for each of the 146 comparisons.

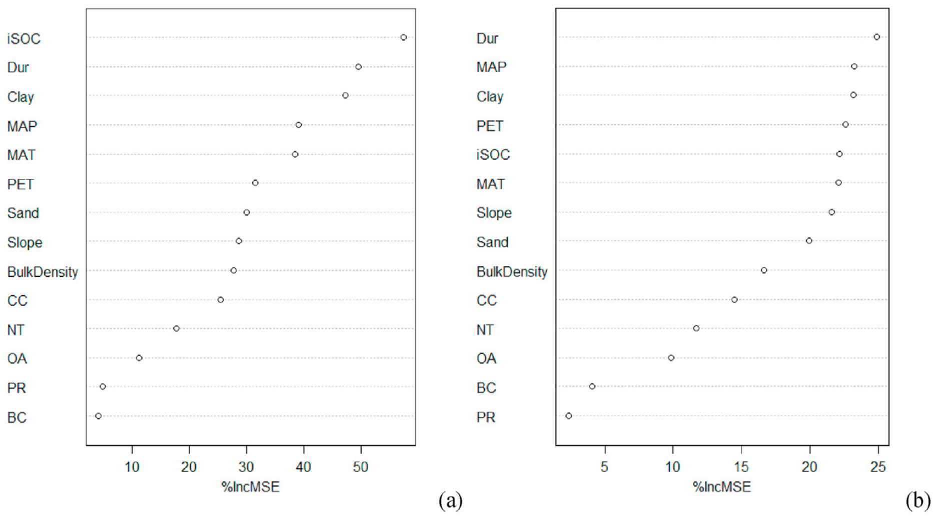


Fig. 2. Variable importance in predicting the SOC stock rate of change (a) and the SOC sequestration rate (b) derived from the RF regression. (iSOC = initial SOC stock, Dur = duration of the field experiment, Clay = percentage of clay in the soil, MAP = mean average precipitation, MAT = mean average temperature, PET = potential evapotranspiration of the soil, Sand = percentage of sand in the soil, Slope = slope where the field experiment was conducted, BulkDensity = bulk density of the soil, CC = cover cropping, NT = no-tillage, OA = organic amendments, PR = returning pruning residues to the soil, and BC = biochar amendments).

$$AP_{country} = \sum_{i=1}^{n} area_i \times AR_i \tag{10}$$

3. Results and discussion

3.1. Random forest performance in predicting changes in SOC stocks under SCS management

3.1.1. RF tuning

Results from the model tuning showed that a m_{try} value of 6 combined with a n_{tree} value of 3,500 produced the lowest OOB error rate (0.06%) for the SOC stock rate of change. For the SOC sequestration rate, a m_{try} value of 3 combined with a n_{tree} value of 1,500 generated the lowest OOB error rate (36.6%). These values were, therefore, selected as input parameters to train the RF regression for the two response variables.

3.1.2. RF accuracy and prediction performance

Indicators showing the performance of the model for the two response variables are presented in Table 1. The RMSE and MAE values obtained for the SOC stock rate of change were 0.03 and 0.02, respectively, whereas those found for the SOC sequestration rate were 1.65 and 0.92, respectively. The different explanatory variables used to build the RF regression explained 58 and 52% of the variation for the SOC stock rate of change and the SOC sequestration rate, respectively.

The prediction performance of the RF model is represented in Fig. 1 for the two response variables. Predicted values of the SOC stock rate of change (Fig. 1(a)) were associated with a higher accuracy overall than those of the SOC sequestration rate (Fig. 1(b)). NRMSE values (50% for the SOC stock rate of change and 85% for the SOC sequestration rate) confirmed that the prediction accuracy of the model was higher with the SOC stock rate of change than with the SOC sequestration rate, since NRMSE values close to 40% are satisfactory, while values above 71% are not considered accurate (Hengl, 2007). The SOC stock rate of change was, therefore, preferentially used over the SOC sequestration rate as a response variable in this study.

The prediction performance of the RF regression was satisfactory. The R^2 value of 0.58 compared with the previous study by Were et al. (2015), whose RF regression predicted SOC stocks in western Kenya with an R^2 value of 0.53. It was also similar to the R^2 of 0.51 obtained by Aksoy et al. (2012), though they used a hybrid Regression-Kriging method to predict SOC stocks in Crete, Greece, instead of a RF regression. This suggests that RF regression is an adequate tool for predicting the SOC stock rate of change over time depending on different soil management options. The prediction performance of our model was, however, somewhat lower than several previous studies using RF regression to predict SOC stocks in various regions (*e.g.*, $R^2 = 0.82$, Sreenivas et al., 2016; $R^2 = 0.74$, Wiesmeier et al., 2011; and $R^2 = 0.71$, Viscarra Rossel and Behrens, 2010), though This was substantially higher than many other studies (*e.g.*, $R^2 = 0.18$, Gastaldi et al., 2012; $R^2 = 0.23$, Dharumarajan et al., 2017; and $R^2 = 0.29$, Gray et al., 2009). The fact that other studies found higher R^2 when predicting SOC stocks with RF might be due to the different extents of the study areas (local or regional vs. global) or to the quality of the auxiliary input data used to train the RF (Were et al., 2015). The high variability of the soil properties used as explanatory variables could also be a factor explaining lower R^2 values (Dharumarajan et al., 2017).

The prediction performance found in this study was coherent with the fact that R^2 values greater than 0.7 tend to be unusual in the case of quantitative soil spatial models, whereas values equal to or lower than 0.5 are more common (de Carvalho et al., 2014). The prediction performance of RF regression for SOC stock predicting and mapping also varies importantly from study to study, with reported values as low as 0.18 (Gastaldi et al., 2012) and as high as 0.82 (Sreenivas et al., 2016). This suggests that the prediction accuracy of RF models might depend on whether the explanatory variables taken into account to build the regression can model effectively the spatial variability of the response variable (Sreenivas et al., 2016). The fact that the R^2 in this study was not as high as in other studies could be because the input variables used to build the RF regression did not model the full extent of the spatial variability of the SOC stock rate of change. However, it is important to highlight that the other studies used as comparisons to assess the prediction performance of our model predicted SOC stocks from input parameters at a specific time in a particular region, and not changes in SOC stocks over time due to changes in soil management.

3.1.3. Importance of explanatory variables for predicting changes in SOC stocks

The variable importance varied notably between the two response variables modelled (Fig. 2). The initial SOC content was the most important variable in explaining the SOC stock rate of change, since it was associated with the highest %IncMSE (Fig. 2(a)). The duration of the field experiment was slightly less important, but still of major dominance, while the percentage of clay in the soil was the third most important variable in explaining the SOC stock rate of change. The duration of the field experiment played the most important role in the model accuracy for the SOC sequestration rate, followed by the mean average precipitation and the percentage of clay in the soil (Fig. 2(b)). This suggests that some of the explanatory variables had a very different weight in explaining the variation in the change in SOC stocks depending on the response variable: for instance, the initial SOC content, though the most important variable for the SOC stock rate of change, was classified

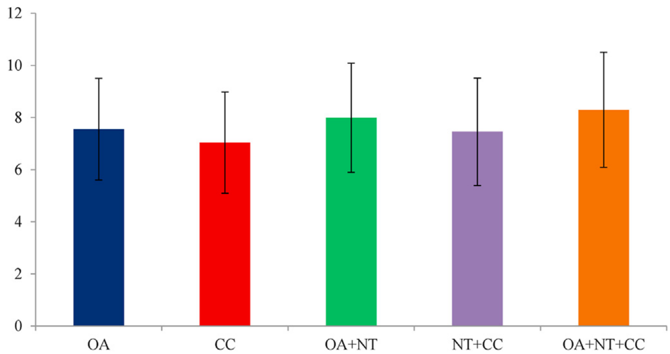


Fig. 3. Average abatement rate (in Mg CO_2-eq. ha^{-1} yr^{-1}) per SCS practice. Error bars represent standard deviation.

as the fifth most important variable for the SOC sequestration rate.

3.2. *Abatement rate and potential of viticultural land under SCS management*

3.2.1. *Abatement rates under SCS management*

There were some differences between the abatement rates of the five SCS practices modelled in this study (Fig. 3). OA+NT+CC was associated with the highest abatement rate, followed by OA+NT, OA, NT+CC and, lastly, CC. The overall abatement rate of OA+NT+CC was 8.29 Mg CO_2-eq. ha^{-1} yr^{-1} (Fig. 3), which was 10% and 18% higher than that of OA and CC, respectively, and 4% and 11% higher than that of OA+NT and NT+CC, respectively. The use of this particular combination of SCS practices has not been, to our knowledge, modelled before in the context of viticultural soils, but vineyards have been taken into account in a few meta-analyses performed for broader cropping systems. Aguilera et al. (2013) found an abatement rate of 4.07 Mg CO_2-eq. ha^{-1} yr^{-1} in Mediterranean cropping systems under OA+NT+CC management. This value is smaller than that found in this study, which suggests that vineyards show a particularly high SOC response under OA+NT+CC comparatively to other cropping systems. OA+NT+CC is, thus, a recommended management option for soil carbon sequestration in Western European vineyards.

On average across all winegrowing regions, OA was associated with an abatement rate of 7.55 Mg CO_2-eq. ha^{-1} yr^{-1} (Fig. 3). This was substantially higher than the abatement rate obtained in other studies for the same practice: Bleuler et al. (2017) predicted, using the RothC model, an abatement rate of 0.81 Mg CO_2-eq. ha^{-1} yr^{-1} (0.22 Mg C ha^{-1} yr^{-1}) for compost amendment in vineyards of the Foggia province in Italy and a period of 20 years; Mondini et al. (2012) observed an abatement rate of 2.06 Mg CO_2-eq. ha^{-1} yr^{-1} (0.56 Mg C ha^{-1} yr^{-1}) for compost amendment in Italian vineyards, using the RothC model. These differences might be due to the fact that, in the study by Bleuler et al. (2017), compost was introduced only where it is usually used under conventional practice (*i.e.* not in vineyards), and to the fact that Mondini et al. (2012) considered the effects of climate change into their modelling. They may also be because these two studies only focused on compost amendment, while all types of organic amendments have been taken into account in this study (*i.e.* manure, sludge, straw, bark, mushroom substrate, leonardite, microbial fertiliser); different types of organic amendments might have different impacts on OC accumulation in the soil and be applied in higher quantities than compost amendments. OA is, therefore, an effective practice to increase SOC sequestration in Western European vineyards.

The use of CC yielded an average abatement rate of 7.03 Mg CO_2-eq. ha^{-1} yr^{-1} (Fig. 3). It was notably higher than that found in previous studies: in the study by Bleuler et al. (2017), the abatement rate of CC in the Foggia province was estimated, using the RothC model, at 2.02 Mg CO_2-eq. ha^{-1} yr^{-1} (0.55 Mg C ha^{-1} yr^{-1}), while in the study by Pardo

Table 2
Average abatement rate (in Mg CO_2-eq. ha^{-1} yr^{-1}) of each country and winegrowing region for the five SCS practices modelled.

Winegrowing region	OA	CC	OA+NT	NT+CC	OA+NT+CC
Spain	6.54	6.28	6.73	6.50	7.06
Andalusia	5.18	4.57	5.54	4.94	5.59
Aragon	7.42	7.26	7.59	7.46	8.08
Basque Country	12.71	12.54	13.80	13.57	14.65
Canary Islands	16.45	15.60	16.89	16.20	17.53
Castile and León	7.42	7.11	7.53	7.24	7.94
Castilla-La Mancha	5.86	5.76	5.96	5.91	6.31
Catalonia	6.99	6.30	7.37	6.68	7.57
Extremadura	4.31	3.73	4.58	4.00	4.56
Galicia	12.47	12.19	12.99	12.76	13.87
La Rioja	9.05	8.62	9.50	9.01	9.91
Madrid	7.92	7.74	8.00	7.88	8.51
Mallorca	7.55	6.47	8.08	7.00	8.09
Murcia	6.71	6.53	6.85	6.74	7.22
Navarre	7.64	7.28	8.08	7.65	8.47
Valencia	7.28	7.15	7.42	7.35	7.90
France	7.68	7.02	8.22	7.52	8.52
Alsace-Lorraine	11.17	10.71	11.74	11.26	12.23
Beaujolais	8.71	8.44	9.24	8.97	9.79
Bordeaux	6.76	6.10	7.17	6.50	7.44
Bugey	13.27	12.96	14.33	13.93	14.99
Burgundy	8.94	8.48	9.62	9.11	10.02
Champagne	9.34	8.66	9.90	9.16	10.16
Cognac	6.81	6.22	7.43	6.79	7.69
Corsica	8.74	8.10	9.21	8.61	9.59
Jura	12.60	12.22	13.76	13.24	14.31
Languedoc	8.09	7.40	8.70	7.92	8.97
Loire Valley	5.34	4.64	5.58	4.84	5.75
Provence	7.76	7.00	8.37	7.58	8.65
Rhône Valley	8.22	7.53	8.80	8.08	9.19
Roussillon	7.08	6.37	7.46	6.73	7.63
Savoy	11.76	11.52	12.51	12.26	13.23
South-West	7.44	6.75	8.02	7.29	8.37
Italy	7.78	7.15	8.41	7.72	8.63
Abruzzo	7.46	6.66	8.11	7.22	8.22
Aosta Valley	13.50	13.54	13.76	13.90	14.79
Apulia	6.96	6.18	7.34	6.54	7.38
Basilicata	7.05	6.22	7.61	6.71	7.72
Calabria	6.65	5.81	7.12	6.31	7.31
Campania	8.20	7.55	8.92	8.24	9.24
Emilia-Romagna	8.85	8.46	9.82	9.26	10.22
Friuli Venezia Giulia	8.76	8.49	9.64	9.27	10.15
Lazio	7.79	7.00	8.45	7.65	8.69
Liguria	10.62	10.23	11.51	11.04	12.03
Lombardy	8.91	8.60	9.88	9.41	10.32
Marche	7.56	6.93	8.25	7.45	8.44
Molise	9.41	8.77	9.73	9.11	10.02
Piedmont	8.58	8.17	9.53	8.95	9.92
Sardinia	7.65	6.82	8.04	7.26	8.20
Sicily	7.12	6.23	7.67	6.80	7.71
Trentino-South Tyrol	11.38	11.29	11.79	11.76	12.58
Tuscany	8.18	7.63	8.94	8.26	9.21
Umbria	8.34	7.69	9.00	8.22	9.18
Veneto	8.07	7.77	8.87	8.48	9.34
Portugal	8.45	7.87	8.82	8.29	9.27
Alentejo	5.74	5.08	6.03	5.38	6.15
Algarve	7.28	6.40	7.67	6.83	7.82
Beira atlântico	9.47	8.75	10.08	9.40	10.55
Beira interior	8.72	8.19	8.92	8.43	9.45
Dão	10.48	9.97	10.82	10.40	11.44
Douro Valley	9.04	8.62	9.41	9.05	9.98
Lisbon	7.84	7.10	8.38	7.69	8.70
Madeira	12.11	11.29	12.73	11.95	13.08
Minho	11.36	10.98	11.80	11.47	12.50
Setúbal	6.02	5.31	6.14	5.48	6.35
Tejo	6.97	6.06	7.22	6.34	7.40
Terras de Císter	9.50	9.18	9.73	9.49	10.41
Transmontano	8.83	8.40	9.07	8.70	9.65

(*continued on next page*)

Table 2 (*continued*)

Winegrowing region	OA	CC	OA+NT	NT+CC	OA+NT+CC
Germany	10.61	10.04	11.18	10.58	11.57
Ahr	14.48	14.16	14.72	14.47	15.31
Baden	13.41	12.93	14.24	13.75	14.92
Franconia	10.41	9.75	11.04	10.31	11.32
Hessische Bergstrasse	10.08	9.50	10.57	10.02	11.05
Mittelrhein	13.03	12.60	13.52	13.11	14.06
Mosel	12.45	12.11	12.88	12.61	13.53
Nahe	10.73	10.06	11.29	10.57	11.54
Palatinate	8.88	8.33	9.27	8.69	9.56
Rheingau	10.70	10.06	11.27	10.58	11.53
Rheinhessen	9.61	8.91	10.23	9.42	10.41
Saale-Unstrut	11.76	10.98	12.48	11.61	12.71
Saxony	13.85	13.19	14.03	13.41	14.42
Württemberg	9.70	9.12	10.32	9.72	10.73
Austria	8.99	8.41	9.47	8.82	9.72
Burgenland	8.31	7.75	8.70	8.07	8.93
Lower Austria	9.04	8.44	9.54	8.86	9.77
Styria	11.73	11.31	12.50	12.08	13.06
Vienna	8.60	7.95	9.02	8.31	9.25

et al. (2017), the same practice in vineyards along the Spanish Mediterranean coast had an abatement rate of 1.91 Mg CO_2-eq. ha^{-1} yr^{-1} (0.52 Mg C ha^{-1} yr^{-1}). The abatement rate of CC in our study was, however, lower than that reached under OA, which could be due to the fact that, in the case of CC, the carbon input comes from inside the vineyard agroecosystem and is, therefore, limited by the primary productivity of the vineyard, whereas, in the case of OA, it comes from outside the vineyard and is usually more substantial. Despite this, the use of CC remains a strategic SCS practice in vineyards of Western Europe considering its potential contribution to SOC sequestration, while providing additional benefits in terms of soil quality and winegrowing, such as reducing nutrient loss due to leaching and lowering soil evaporation by increasing soil moisture in the upper layer during critical phases of the grapevine cycle (Monteiro and Lopes, 2007).

The average abatement rates of OA+NT and NT+CC were 7.99 Mg CO_2-eq. ha^{-1} yr^{-1} and 7.45 Mg CO_2-eq. ha^{-1} yr^{-1}, respectively (Fig. 3). The use of NT in combination with OA or CC resulted in higher abatement rates (by +6% in both cases) than when the practices were implemented with tillage. This shows that the absence of tillage, when combined with OA or CC, is effective in reducing carbon losses and leads to an even greater carbon accumulation in viticultural soils.

Even though OA, CC, OA+NT, NT+CC and OA+NT+CC are associated with high abatement rates, their adoption may lead to varying implementation and maintenance costs, which may impact their cost-effectiveness: adopting NT may require capital investment in new equipment, but may lead to a reduction in fuel and time costs; CC may induce additional input and time costs; and the use of OA may be associated with labour and time costs, in addition to costs related to the purchase of organic amendments (Sykes et al., 2020). A cost-effectiveness analysis of the adoption of these SCS practices in Western European vineyards is, thus, needed to evaluate which practices or combination of practices are the most cost-effective while still allowing for high amounts of OC to be sequestered in the soil.

3.2.2. *Abatement rates in viticultural soils under SCS management at the regional and national level*

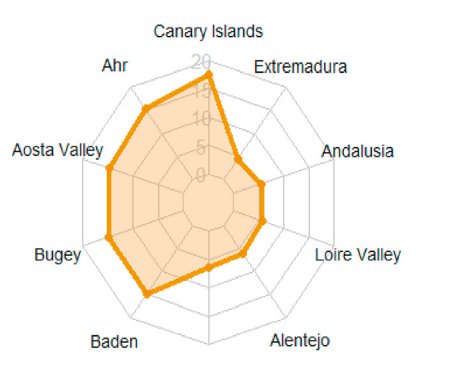
The average abatement rates in viticultural soils at the regional and national level of Spain, France, Italy, Portugal, Germany and Austria are presented in Table 2. There were notable variations in the abatement rate between winegrowing regions and SCS practices.

At the regional level, the adoption of CC in the Extremadura winegrowing region led to the lowest abatement rate (3.73 Mg CO_2-eq. ha^{-1} yr^{-1}), whereas the Canary Islands were associated with the highest abatement rate (17.53 Mg CO_2-eq. ha^{-1} yr^{-1}) under OA+NT+CC (Table 2). The abatement rate in the Canary Islands under OA+NT+CC was approximately 4.7 times higher than in Extremadura under CC. The abatement rate of the five SCS practices followed a similar pattern in all winegrowing regions, with OA+NT+CC being associated with the highest abatement rate, followed by OA+NT, OA or NT+CC, and finally CC. Overall, the Canary Islands, Ahr, the Aosta Valley, Bugey and Baden were the five winegrowing regions associated with the highest abatement rates across all SCS practices, whereas Extremadura, Andalusia, the Loire Valley, Alentejo and Setúbal were the five winegrowing regions associated with the lowest abatement rates (Table 2). The abatement rates obtained for these regions under OA+NT+CC are represented in Fig. 4(a).

At the national level, the lowest abatement rate (6.28 Mg CO_2-eq. ha^{-1} yr^{-1}) was found in Spain under CC, while the highest abatement rate (11.57 Mg CO_2-eq. ha^{-1} yr^{-1}) was reached in Germany under OA+NT+CC (Table 2). The abatement rates of the five SCS practices followed the same pattern at the national level as they did at the regional level. Overall, Germany was the country associated with the highest abatement rates, followed by Austria, Portugal, Italy, France and finally Spain (Table 2). The abatement rates of the six countries under OA+NT+CC are represented in Fig. 4(b).

3.2.3. *Abatement potential of viticultural land in Western Europe*

The abatement rates presented in Table 2 did not take into account the size of the viticultural land in a given winegrowing region or country; as a result, some very high values of abatement rate, if reached in small winegrowing regions, could have the same or a lower cumulated impact on SOC sequestration than lower abatement rates in larger winegrowing regions. This is why it is crucial to contextualise the abatement rate in relation to the total viticultural land in a winegrowing region or country. The abatement potential of viticultural land at the national level is



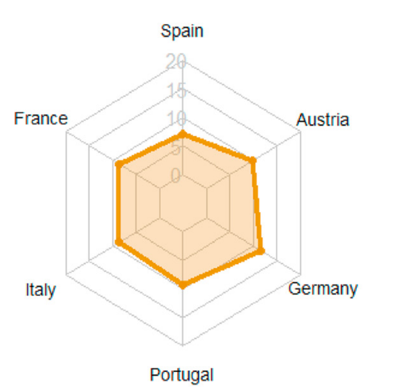


Fig. 4. Average abatement rate (in Mg CO_2-eq. ha^{-1} yr^{-1}) under OA+NT+CC at the regional level (a) and the national level (b).

Table 3
Abatement potential (in Tg CO_2-eq. yr^{-1}) of the total viticultural land of Spain, France, Italy, Portugal, Germany and Austria for the five SCS practices, supposing that each SCS practice is adopted by all winegrowers in all vineyards. These predictions are valid for a period of 20 years and a soil depth of 30 cm. The viticultural land area (in Mha) is also given for each country as of 2018.

Winemaking country	OA	CC	OA+NT	NT+CC	OA+NT+CC	Area (Mha)
Spain	6.34	6.09	6.52	6.30	6.84	0.969
France	6.09	5.57	6.52	5.96	6.76	0.793
Italy	5.48	5.04	5.93	5.44	6.08	0.705
Portugal	1.62	1.51	1.69	1.59	1.78	0.192
Germany	1.09	1.03	1.15	1.09	1.19	0.103
Austria	0.44	0.41	0.46	0.43	0.48	0.049
Total	21.06	19.65	22.27	20.81	23.13	2.81

presented in Table 3 for the six countries. Results showed that, though abatement rates in German winegrowing regions were consistently higher than in almost all other European winegrowing regions, the abatement potential of the total viticultural land in Germany was remarkably lower than in Spain, France and Italy, as the German viticultural land is much smaller than that of the other countries. The same was true for Austria, whose abatement potential was the lowest overall, even though the abatement rates in Austria were higher than those in Spain, France and Italy. Nevertheless, values presented in Table 3 were calculated under the assumption that all winegrowers would implement the SCS practice in all vineyards. In reality, the abatement potential of the total viticultural land depends on the extent to which SCS practices have already been implemented in vineyards in each winegrowing region. For example, in France, OA is used at least once every fourth year on 27% of the total viticultural land (Agreste, 2017), which means that a more accurate estimate of the total abatement potential for viticulture in France under OA would be 4.45 Tg CO_2-eq. yr^{-1}, instead of 6.09. Investigating the adoption rate of SCS practices in vineyards is, thus, needed to better evaluate the abatement potential of winegrowing regions.

3.3. Spatial distribution of abatement rate in Western European vineyards under SCS management

Maps displaying the abatement rate of viticultural land in Western Europe under the five SCS practices modelled are presented in Appendix A. The change in SOC stocks under SCS management tended to follow similar patterns within winegrowing regions but to a different extent depending on the practices implemented (*e.g.*, the vineyards associated with very high abatement rates were hotspots under all SCS practices, but with varying abatement rates under each SCS practice). In this section, we focus more specifically on maps representing the adoption of OA in the Mediterranean region of France (Fig. 5) and CC in western Germany (Fig. 6). These two case studies provided a useful insight into the variations in abatement rate within winegrowing regions.

The impacts of OA adoption on SOC sequestration were shown in vineyards located in the Mediterranean region of France (Fig. 5). The winegrowing regions of Roussillon, Languedoc and Provence appear in Fig. 5, as well as the southern half of the Rhône Valley. The distribution of abatement rate was very heterogeneous throughout the Mediterranean region of France, with a succession of patches of high (up to 25.87 Mg CO_2-eq. ha^{-1} yr^{-1}), medium (round 8 Mg CO_2-eq. ha^{-1} yr^{-1}) and low (down to 4.18 Mg CO_2-eq. ha^{-1} yr^{-1}) abatement rate present within each winegrowing region.

The influence of CC was shown in vineyards of western Germany, in the winegrowing regions of Mosel, Mittelrhein, Rheingau, Rheinhessen, Nahe, Palatinate, Hessische Bergstrasse, Württemberg and Franconia, and in parts of Baden (Fig. 6). The change in SOC stocks under CC was rather homogeneous throughout western Germany, which was

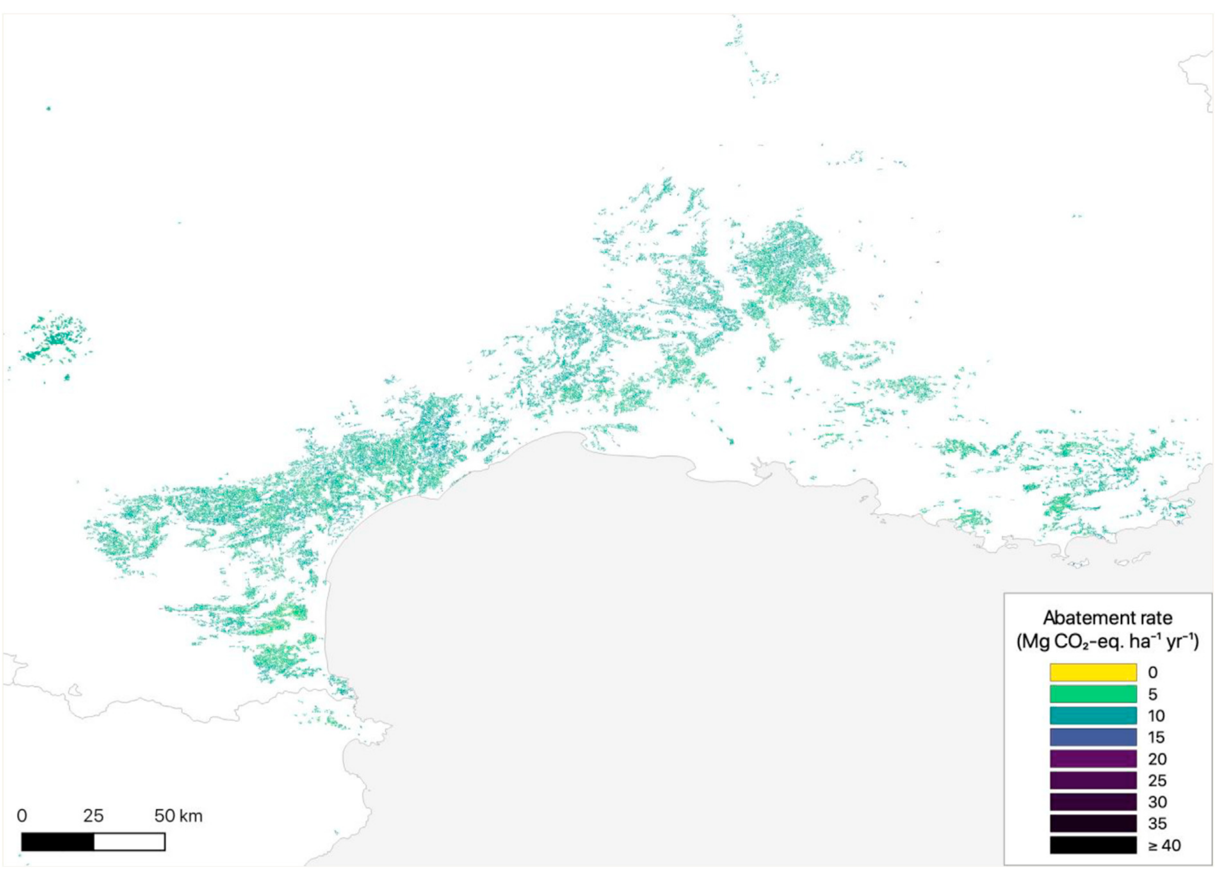


Fig. 5. Abatement rate of OA in viticultural soils in south-eastern France.

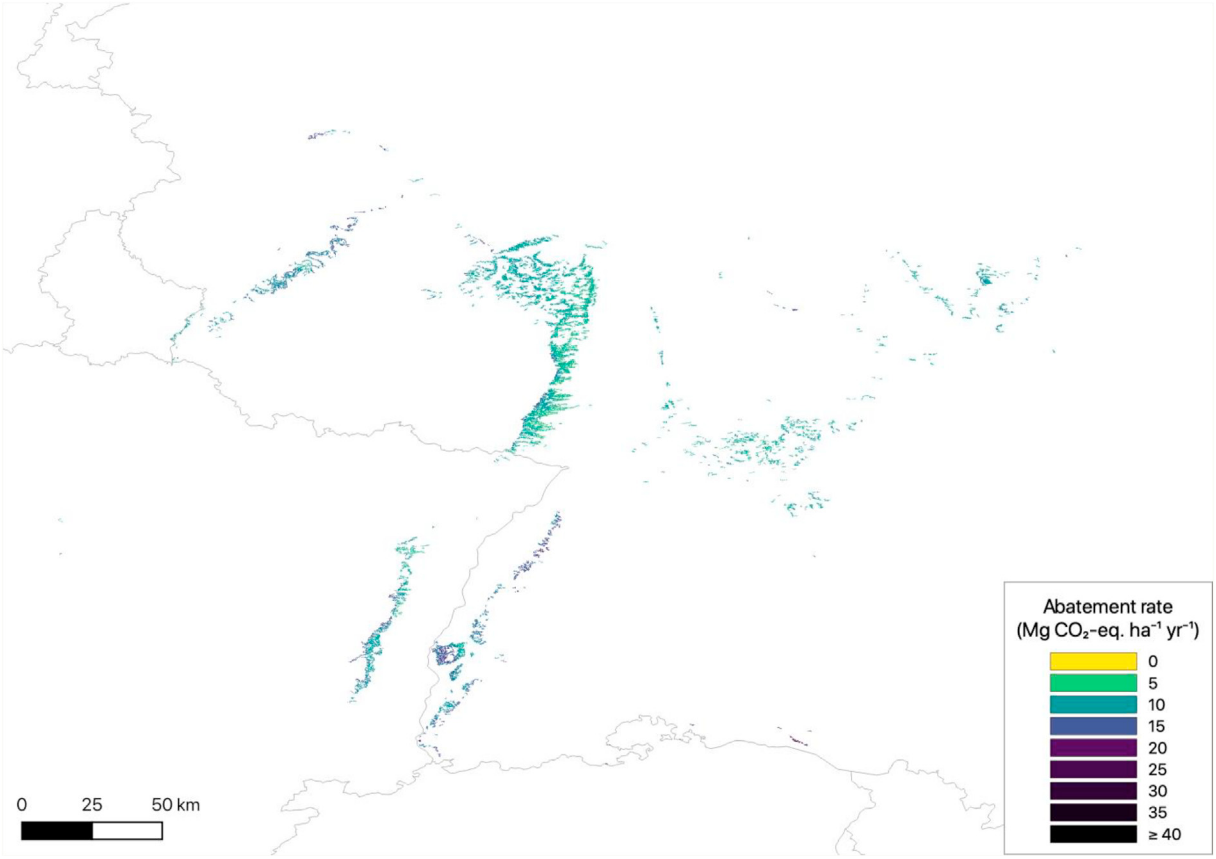


Fig. 6. Abatement rate of CC in vineyards of western Germany.

associated with high values of abatement rate overall. The abatement rate did not vary much within each winegrowing region either, despite a few exceptions: it was slightly lower on the eastern section of the Palatinate and Rheinhessen winegrowing regions, while it was extremely high in southern Baden, with areas where the abatement rate was higher than 30 Mg CO_2-eq. ha^{-1} yr^{-1} and, in a few vineyards, higher than 40 Mg CO_2-eq. ha^{-1} yr^{-1}.

In both Mediterranean France and western Germany, areas with high abatement rate values were characterised by lower bulk density and higher initial SOC content than in areas with lower abatement rates. This shows that viticultural soils with already relatively high SOC stocks have not reached their saturation capacity under current practices and are able to further increase their SOC levels. However, increasing SOC content in these areas may trigger a substantial decrease in bulk density, since there is a negative relationship between SOC concentration and bulk density (Ruehlmann and Körschens, 2009). If bulk density decreases below 1,000 kg m^{-3}, soils become carbon-dense and are considered likely to lose SOC no matter the type of soil management implemented (Zomer et al., 2017). There is, therefore, a need to further develop SOC change modelling in viticultural soils under SCS management, so changes in soil parameters induced by changes in SOC stocks are also taken into account.

3.4. Gaps and uncertainty of modelling applications

The number of comparisons for each SCS practice varied between treatments. While a high number of observations was found for some SCS practices (*e.g.*, 70 observations for NT+CC), others presented a substantially lower number of observations (*e.g.*, BC had 4 observations). This indicated that the prediction accuracy of the model differed depending on the SCS practice considered. That is why only the SCS practices with the highest number of observations were modelled and mapped in this paper: OA (n = 27), CC (n = 9), OA+NT (n = 6), NT+CC (n = 70) and OA+NT+CC (n = 7). However, there was still a strong difference in accuracy between these five options, since the number of observations for NT+CC and OA was 11.7 and 4.5 times higher than that for OA+NT, respectively, 7.8 and 3 times higher than that for CC, respectively, and 10 and 3.9 times higher than that for OA+NT+CC, respectively.

The quality of the auxiliary data used for predicting the SOC stock rate of change varied depending on the accuracy of the raster files used to extract the data. For instance, the raster files used to retrieve input data on Initial SOC stock, Clay, Sand and Bulk density had a resolution of 250 m × 250 m, while the resolution for PET was 1 km × 1 km, which makes the accuracy of extracted Initial SOC stock, Clay, Sand and Bulk density higher than that of PET. In addition, the raster databases used to estimate the Slope variable had quite a low accuracy, as they were built by giving, for each cell, the percentage of land falling within a specific slope category, with a 10 km × 10 km resolution. The accuracy of the predictions could be improved by increasing the quality of the auxiliary data and, for example, by increasing the resolution of the raster files to 100 m × 100 m to match the resolution of the CORINE Land Cover.

4. Conclusions

Modelling results demonstrated that RF regression was a satisfactory method for predicting changes in SOC stocks associated with SCS management in vineyards. The SOC stock rate of change was used as a response variable in the model to optimise prediction accuracy and model performance. The initial SOC content was the most important variable explaining the observed variability in the SOC stock rate of change under SCS management: having reliable data on vineyards' SOC stocks is, therefore, essential to ensure that model predictions have high accuracy. Overall, the model created in this study had a good prediction accuracy ($R^2 = 0.58$; RMSE = 0.03); it could serve in further studies as a predictive tool to quantify the abatement rate of SCS practices in vineyards in countries with important winegrowing regions in the other Member States of the European Union (*e.g.*, Romania) or in other parts of the world (*e.g.*, the USA).

The predictions of changes in SOC stocks following the adoption of SCS management suggested that OA+NT+CC was the practice associated with the highest abatement rate across all winegrowing regions, with values ranging from 4.56 Mg CO_2-eq. ha^{-1} yr^{-1} in Extremadura (Spain) to 17.53 Mg CO_2-eq. ha^{-1} yr^{-1} in the Canary Islands (Spain). The other SCS practices also yielded high abatement rates, though to a lesser extent. The results of this paper can serve to inform policymaking regarding the adoption of SCS practices at the European level and, more particularly, in the viticulture sector. Further research is needed, however, to evaluate the cost-effectiveness of the different SCS practices taken into account in this study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cesys.2021.100024.

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